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INNOVATION DIFFUSION MODELS OF NEW PRODUCT ACCEPTANCE:
A REEXAMINATION

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by

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and

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INTRODUCTION

Product sales, especially those of new products, are influenced by many factors — both internal and external to the selling organization and both controllable and uncontrollable (Urban and Hauser 1980; Wind, Mahajan and Cardozo 1981).

Due to the enormous number and complexity of such factors, it is not surprising that product failure rates are relatively high. Indeed, new product failure rates have variously been reported in the range 40-90%. (Crawford 1977).

Still, such a situation has not deterred marketing researchers from developing and designing techniques to predict and/or explain the levels of new product sales over time (Mahajan and Muller 1979). Most new product sales prediction or estimation models differ in the number and types of behavioral and decision variables considered, the type of data and level of data aggregation, and the degree of mathematical sophistication (Wind 1982). Chambers, Mullick and Smith (1971), for example, identify three types of sales forecasting methods — qualitative methods (e.g. the Delphi method), time-series analysis and projection (e.g. Box-Jenkins methods), and causal methods (e.g. econometric models). Causal methods of sales forecasting also include models that are based on product life cycle analysis and implicitly assume that new product acceptance by various buying groups such as innovators, early adopters, early majority, late majority and laggards follows an S-shaped (or exponential) curve (Rogers 1983). In other words, new product diffusion, in terms of the cumulative number of adopters over time, follows an S-shaped curve. Evidence for such a generalized new product acceptance regularity has been found in a number of innovation diffusion studies in marketing (Midgley 1977; Robertson 1971; Gatignon and Robertson 1985).

To model the growth of a new product, management can resort to one of the two analytical frameworks (Lilien and Kotler 1983). It can consider new product sales in terms of the diffusion process or in terms of the adoption process. The diffusion process is concerned with the spread of a new product from its manufacturer to ultimate users or adopters. The adoption process, on the other hand, refers to the sequence of stages through which a consumer progresses from first awareness of an innovation to final acceptance. Adoption is equivalent to product purchase in the case of nonrepurchasable products. For repurchasable or frequently purchased products, adoption represents commitment and continued use of the product over time. The adoption process framework has been utilized to evaluate the potential viability of a new product at the pre-test and test-market stages of the new production introduction process (Silk and Urban 1978; Blattberg and Golanaty 1978; Pringle, Wilson and Brody 1982; Narasimhan and Sen 1983). The pre-test and test-market sales evaluation models, commonly developed for frequently purchased products, generally provide an ultimate market share that the new product can be expected to capture rather than an explicit life cycle curve specifying product penetration over time.

All new products, whether they are purchased once, occasionally, or frequently, have in common a first-purchase sales volume curve. The focus of diffusion models is generally on the generation of the product life cycle to forecast the first-purchase sales volume. Most of these models have their roots and analogies in the models of epidemics or in biology and ecology (Bailey 1957; Lotka 1956; Pearl 1925; Peilou 1969) and serve the purpose of forecasting sales for durable goods and novelty items. One of the underlying behavioral premises in the development of these models is that new product

acceptance is an imitation process; that is, a new product is first adopted by a select few innovators who, in turn, "influence" others to adopt it. It is the "interaction" between adopters (innovators) and nonadopters (non-innovators or imitators) that is posited to account for the rapid growth stage in the product diffusion process. The best known first-purchase diffusion models of new product acceptance in marketing include the Bass model (Bass 1969), the Fourt-Woodlock model (Fourt and Woodlock 1960) and the Mansfield model (Mansfield 1961). The Bass model and its revised forms have been successfully demonstrated in retail service, industrial technology, agriculture, educational and consumer durables sectors (Bass 1969; Dodds 1973; Nevers 1972; Lekvall and Watkins 1973; Lawton and Lawton 1979; Tigert and Farivar 1981), and the Fourt-Woodlock model has been used to study success of certain new grocery products (Fourt and Woodlock 1960). The Mansfield model and its revised forms, such as those proposed by Blackman (1974), Fisher and Pry (1971) and Sharif and Kabir (1976), have been used in technological substitution studies of industrial innovations (Hurter and Rubenstein 1978; Linstone and Sahal 1976)).

In recent years a number of efforts have been made to extend these models to better understand and predict the spread of a new product in the marketplace (for a review, see Mahajan and Peterson (1985)). Despite these extensions, however, the viability of diffusion models to forecast the new product growth has been challenged. Bernhardt and Mackenzie (1972), for example, have stated that in some cases the simple diffusion models work well and in other cases the results are not so good. They suggest that the success of diffusion models has been due to "judicious choice of situation, population, innovation

and time frame for evaluating the data". Heeler and Hustad (1980) report examples of new product diffusion in an international setting where the Bass model does not perform well.

Given these and other challenges, for a practitioner, the appropriate question is why do the diffusion models work in some cases and do not perform well in others. The objective of this paper is to respond to this question. In responding to this question, we also hope to provide a brief critical overview of the current diffusion modeling literature along with directions for future research.

A REEXAMINATION

In order to respond to the question as to why do diffusion models work in some cases and do not perform well in others, we examine this issue in the following five problem areas: (1) structure of basic diffusion models, (2) data used to calibrate the diffusion models, (3) estimation procedures employed to specify the diffusion model parameters, (4) relaxation of other relevant assumptions and, (5) possible uses of diffusion models.

Structure of Basic Diffusion Models

In his 1969 article Bass suggested that the following differential equation can be used to represent the diffusion process:

$$\frac{dN(t)}{dt} = (p + \frac{q}{m} N(t)) (m - N(t)) \quad (1)$$

where $N(t)$ is the cumulative number of adopters at time t , m is the ceiling, p is the coefficient of innovation and q is the coefficient of imitation. Assuming $F(t) = \frac{N(t)}{m}$, the fraction of the potential adopters who adopt the product by time t , the Bass model can be restated as:

$$\frac{dF(t)}{dt} = (p + q F(t)) (1 - F(t)) \quad (2)$$

If $p = 0$, equation (2) yields the Mansfield model and if $q = 0$, equation (2) reduces to the Fourt-Woodlock model. Furthermore, if $F(t = t_0 = 0) = 0$, simple integration of equation (2) gives the following distribution function to represent the time-dependent aspect of the diffusion process. That is,

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \quad (3)$$

or

$$N(t) = m F(t) \quad (4)$$

Equation (3) yields the S-shaped diffusion curve captured by the Bass model. In fact, for this curve, the point of inflection (i.e., the maximum penetration rate, $\left(\frac{dF(t)}{dt}\right)_{\max}$) occurs when

$$F(t^*) = \frac{1}{2} - \frac{p}{2q} \quad (5)$$

$$t^* = -\frac{1}{(p+q)} \ln\left(\frac{p}{q}\right) \quad (6)$$

and

$$f(t^*) = \frac{dF(t^*)}{dt} = \frac{q}{4} + \frac{p}{2} + \frac{p^2}{4q} \quad (7)$$

Hence, for a particular product, if p , q and m are known, equations (3) - (7) can be used to represent the product growth curve.

One possible reason why the Bass model works in some cases and does not perform well in others, we believe, is because the Bass model is not flexible enough to accommodate various diffusion patterns. Since $p \geq 0$

and $q \geq 0$,

as is apparent from equation

(5), the Bass model assumes that, for any innovation, the maximum rate of penetration (point of inflection) cannot occur after an innovation has penetrated 50% of its potential market.

It also assumes that for any innovation, the diffusion curve is symmetric. That is, the diffusion pattern after the point of inflection is mirror image of the diffusion pattern before the point of inflection. Given equation (5), $\frac{dF(t)}{dt} = \frac{p}{2} + \frac{q}{4} + \frac{p}{4q} - qk^2$, for $F(t) = F(t^*) + k$ as well as $F(t) = F(t^*) - k$, where k is a constant.

Given the above prespecified restrictions on the shape of the diffusion pattern, it is not surprising that the Bass model does not perform well for

products where the point of inflection occurs beyond 50% penetration and/or the diffusion curve is asymmetric. Related to the Bass model is the Gompertz curve which has also been used to represent the diffusion dynamics (Dixon 1980). The Gompertz curve, although asymmetric, also possesses a fixed point of inflection at $F(t^*) = 0.37$.

In recent years, a number of basic diffusion models have been proposed to overcome the above mentioned structural shortcomings of the Bass model. Examples of these models include the models proposed by Floyd (1968), Sharif and Kabir (1976), Jeuland (1981a) and Easingwood, Mahajan and Muller (1983) (for a review of these models, see Mahajan and Peterson (1985)). Although possessing the desirable structural properties (in terms of point of inflection and asymmetry), these models, unfortunately, do not yield an explicit solution, representing $N(t)$ or $F(t)$ as a function of time and other diffusion parameters, to the differential equation formulations used to specify the diffusion process. In our viewpoint, a relatively little-known diffusion model suggested by Von Bertalanffy (1957) needs to be given a serious

consideration in empirically examining the viability of diffusion models. This model can accommodate both symmetric and nonsymmetric diffusion patterns with a point of inflection that can occur at any time during the diffusion process. As detailed in Mahajan and Peterson (1985), considering only the imitation effect (i.e., $p = 0$), the model hypothesizes that

$$\frac{dF(t)}{dt} = \frac{q}{1-\theta} F^\theta(t) (1 - F^{(1-\theta)}(t)) \quad (8)$$

and

$$F(t) = [1 - (1 - F_0^{(1-\theta)}) e^{-qt}]^{\frac{1}{1-\theta}} \quad (9)$$

where $F(t = t_0 = 0) = F_0$, and θ is a constant. When $\theta = 0$ and $F_0 = 0$, the model reduces to the Fourt-Woodlock model. When $\theta = 2$, equations (8) and (9) yield the Mansfield model. The Von Bertalanffy model is not defined at $\theta = 1$; however, as $\theta \rightarrow 1$, the model reduces to the Gompertz diffusion model. (See the Appendix in Mahajan and Peterson (1985)).

To sum, we believe that one of the reasons that the current Bass type diffusion models work in some cases and do not perform well in others is that the current diffusion models prespecify restrictions on the shape of the diffusion patterns. Like the VonBertalanffy model, we need to develop parsimonious flexible closed-form diffusion models that can accommodate both symmetric and nonsymmetric diffusion patterns with a point of inflection that can occur at any stage of the diffusion process.

Data Used to Calibrate the Diffusion Models

Before using the diffusion models, it is very important to make sure that the models are being applied to the right type of diffusion data. Any S-shaped curve is not a diffusion curve. More specifically, attention needs to be paid to the unit of analysis, sources of data and time interval of the data.

Unit of Analysis: By definition, the basic diffusion models have been developed to represent the conversion of potential adopters to adopters. They are not designed to represent the growth in the unit sales history of a new product unless it is explicitly assumed that each adopter buys or adopts only one unit of the product (in which case number of adopters is equal to the number of units adopted or sold). Consequently, a number of applications of diffusion models in marketing have been limited to adoption of consumer durables among the households. Data contaminated with repeat-purchases, replacements or multipurchases are not appropriate for the basic diffusion models. Consider, for example, the cases of the adoption of ethical drugs by physicians (Lilien, Rao and Kalish 1981) and the adoption of optical scanning equipment by supermarkets (Tigert and Farivar 1981). For ethical drugs, data in general are available on the number of prescriptions written over time rather than the number of physicians prescribing an ethical drug in a particular time period. Although sales history for a new ethical drug, in terms of number of prescriptions written, may depict an S-shaped curve, these data are not appropriate for the basic diffusion models unless an explicit prescribing behavior function can be specified to link or convert number of prescriptions (sales) into the number of physicians. Similarly, while studying the adoption of optical scanning equipment among supermarkets, the appropriate unit of analysis is an individual store rather than a supermarket chain since each supermarket chain can have multiple adoptions, ranging from experimental adoption in one store to complete adoption by all stores. Consequently, before using any diffusion model it is imperative that one establishes the proper unit of analysis.

Sources of Data: Sales data for any product can be based on internal sales (shipments), warehouse withdrawals, retail sales and consumer panel or survey data.

As demonstrated by Wind and Learner (1979), different data sources can provide different sales estimates. Given this situation, depending upon the sources of data used, any diffusion model can be expected to yield different sales predictions. In addition, as will be discussed shortly under the estimation procedures, the source of data used may also determine the appropriate estimation procedure used to develop the parameter estimates of any diffusion model. For example, for panel or survey data it may be desirable to use maximum likelihood estimation procedures (e.g. Schmittlein and Mahajan 1982) which are specifically designed to capture sampling errors. Consequently, before using any diffusion model it is important to understand the various data sources and their consequences prior to the development of sales forecasts.

Time Interval: Diffusion models are time-series models; however, they have been developed primarily to capture only the trend component in the sales history of a new product. In the presence of seasonality or other cyclical effects, diffusion models may not perform well. Consequently, choice of a particular time period (monthly, quarterly or annually) used to measure adoptions can effect the results generated by a diffusion model (See, for example, Tigert and Farivar 1981).

To sum, performance of any diffusion model is clearly dependent upon the type of data used to calibrate the model. The performance is sensitive to the unit of analysis, sources of data and time interval used to represent the diffusion process.

Estimation Procedures Used to Calibrate the Diffusion Models

Another possible reason as to why diffusion models work in some cases and do not perform well in others could be because of a particular estimation procedure used to estimate the parameters of the diffusion models. As summarized by Srinivasan, Mahajan and Mason (1985), to date

four different estimation procedures have been suggested in marketing to estimate the parameters of the diffusion models. These four estimation procedures are: ordinary least squares (OLS) procedure suggested by Bass (1969), maximum likelihood (MLE) procedure suggested by Schmittlein and Mahajan (1982), nonlinear least squares (NLS) procedure suggested by Srinivasan and Mason (1985) and the algebraic estimation (AE) procedure suggested by Mahajan and Sharma (1985). Each one of these procedures has its own advantages and disadvantages and as demonstrated by Srinivasan, Mahajan and Mason, for the same diffusion data, these procedures can yield different parameter estimates, consequently affecting the sales forecasts.

Consider for example, the OLS procedure suggested by Bass. In considering the timing of initial purchase of a new product, Bass has suggested that a discrete analog of equation (1) can be used to estimate parameters p , q , m . That is, if $X(i)$ is the expected number of incremental number of adopters in time interval (t_{i-1}, t_i) , the discrete analog of equation (1) can be written as:

$$\begin{aligned} X(i) &= pm + (q-p) N(t_{i-1}) - \frac{q}{m} N^2(t_{i-1}) + \epsilon(i) \\ &= \alpha_1 + \alpha_2 N(t_{i-1}) + \alpha_3 N^2(t_{i-1}) + \epsilon(i) \end{aligned} \quad (10)$$

where $\alpha_1 = pm$, $\alpha_2 = (q-p)$, $\alpha_3 = -\frac{q}{m}$, $E[\epsilon(i)] = 0$, $\text{Var}[\epsilon(i)] = \sigma^2$ and $\epsilon(i)$ is independent of $\epsilon(j)$ for $i \neq j$. Given regression coefficients $\hat{\alpha}_1$, $\hat{\alpha}_2$ and $\hat{\alpha}_3$, the estimates of the parameters p , q and m can be easily obtained. That is,

$$\hat{p} = \hat{\alpha}_1 / \hat{m} \quad (11)$$

$$\hat{q} = -\hat{m} \hat{\alpha}_3 \quad (12)$$

and

$$\hat{m} = \frac{-\hat{\alpha}_2 - \sqrt{\hat{\alpha}_2^2 - 4\hat{\alpha}_1\hat{\alpha}_3}}{2\hat{\alpha}_3} \quad (13)$$

Once p , q and m have been estimated, equations (3) and (4) can be used to project the diffusion curve. Similarly, this procedure can be used for other diffusion models.

This procedure has several shortcomings. First, in the presence of few time-series data points and multicollinearity between variables ($N(t_{i-1})$ and $N^2(t_{i-1})$), one may obtain parameter estimates which are unstable or possess wrong signs (see, for example, Schmittlein and Mahajan 1982; Tigert and Farivar 1981; Heeler and Hustad 1980; Srinivasan and Mason (1985)). Second, this procedure does not provide standard errors for the parameter estimates since p , q and m are nonlinear functions of α_1 , α_2 and α_3 (Srinivasan and Mason 1985). Third, as pointed out by Schmittlein and Mahajan (1982), since the left side of equation (10) should theoretically be the derivative of $N(t)$ and not the difference represented by $X(t)$, $X(t)$ will underestimate $\frac{dN(t)}{dt}$ for time intervals before the point of inflection and will overestimate after that. That is, this procedure contains a time interval bias since discrete time series data are used for estimating a continuous time model. Fourth, as pointed out by Heeler and Hustad (1980), unimodal time series data can generally be fitted closely by a quadratic Taylor series, equation (10). However, the good fit does not in itself support the reformulation of α_1 , α_2 and α_3 into p , q and m via equations (11) - (13) since alternative behavioral models may be possible whose discrete formulation is given by equation (10).

The maximum likelihood and the nonlinear least squares procedures are designed to overcome some of the shortcomings of the OLS procedures. These

procedures specifically eliminate the time interval bias and provide the standard errors for the parameter estimates. However, as pointed out by Srinivasan and Mason (1985), the maximum likelihood procedure, currently available only for the Bass model, is specifically designed to capture sampling errors. Consequently, this procedure may provide standard errors which are too optimistic or unrealistic. They suggest that the desired parameters, for example for the Bass model, can be obtained by using the following:

$$X(i) = m[F(t_i) - F(t_{i-1})] + \mu_i \quad (14)$$

where $F(t)$ is given by equation (3) and μ_i is an additive error term (with variance σ^2) representing the net effect of sampling errors, excluded variables and misspecification of the distribution function. Based on equations (14) and (3), the parameters can be directly estimated by using nonlinear least squares procedures available in a number of computer packages such as BMD.

Although the maximum likelihood and nonlinear least squares procedures are practically appealing, since the algorithms used in the implementation of these procedures employ various search routines to estimate the parameters, for certain products, the parameter estimates may not converge, the final estimates may be sensitive to starting values for p , q and m or algorithms may not provide a global optimum.

Our recommendation, consequently, is that these procedures should be used in conjunction with some simple estimation procedures which can provide approximate parameter estimates as the starting values. One such procedure, for example, is the algebraic estimation procedure suggested by Mahajan and Sharma (1985). For example, in order to estimate the parameters p , q and m of the Bass model, this procedure requires knowledge (based on actual data, analogs

or management judgments) of the occurrence of the point of inflection described by equations (5) - (7). Dropping the time subscript for simplicity and defining n^* = noncumulative number of adopters at the point of inflection t^* , N^* = cumulative number of adopters at t^* , equations (5) - (7) can be written as:

$$p = \frac{n^*(m - 2N^*)}{(m - N^*)^2} \quad (15)$$

$$q = \frac{n^*m}{(m - N^*)^2} \quad (16)$$

$$t^* = \frac{(m - N^*)}{2n^*} \ln \left(\frac{m}{m - 2N^*} \right) \quad (17)$$

If n^* , N^* and t^* are known, equation (17) can be used to estimate m numerically or by trial and error. Knowing m , p and q can be estimated by equations (15) and (16).

The algebraic estimation procedure is relatively simple but it does require the knowledge of the point of inflection. In fact, Heeler and Hustad (1980) and Tigert and Farivar (1981) have suggested that the stable and robust parameter estimates for the Bass model can be obtained if the data under consideration includes the point of inflection. We endorse the recommendation made by Heeler and Hustad that management judgments or other sources should be used to estimate the point of inflection or the ceiling m (for an application of the incorporation of management judgments to estimate m via multiattribute models into the diffusion models, see Souder and Quaddus (1982)).

To sum, selection of a particular estimation procedure can affect the parameter estimates and consequently the sales forecasts developed from a diffusion model. Although maximum likelihood and nonlinear least squares

procedures are practically appealing, these procedures should be used in conjunction with management judgments and the algebraic estimation procedure.

Relaxation of Other Relevant Assumptions

Several assumptions that underlie the basic diffusion models must be recognized before they are applied or their results are interpreted. Since a number of these assumptions are detailed in Mahajan and Peterson (1985) and are also discussed by Kalish and Sen (1985, inclusion of marketing mix variables into diffusion models), Dolan, Jeuland and Muller (1985, impact of competitive structure on innovation diffusion) and, Eliashberg and Chatterjee (1985, sources of inherent uncertainty in innovation diffusion and stochastic diffusion models), we will briefly summarize and comment on some of these assumptions.

A. Diffusion Process is Binary: The basic diffusion models assume that potential adopters of an innovation either adopt the innovation or they do not adopt it. That is, the process is binary. As a consequence of this assumption, the basic diffusion models do not take into account stages in the adoption process (e.g., awareness, knowledge, etc.). That is, they have been primarily concerned with modeling the flow of customers from potential (unaware) to trial states.

One of the reasons that the diffusion models consider the diffusion process to be binary is that typically these models have been applied to actual sales history of a product where its decomposition into the various adoption states may not be possible (Midgley 1976; Silver 1984). As mentioned earlier, the adoption process framework has been used in the development of pre-test and market-test models of new product introduction (Narashimhan and Sen 1983). These models invariably employ panel or survey data where customers are tracked through the various states of the adoption process to develop an appropriate flow model for each state. Whereas the adoption models capture richness and reality, the diffusion models embrace simplicity and parsimony.

In recent years, however, these two streams of model building seem to be converging. For example, most applications of adoption models (e.g., Urban's SPRINTER 1970) have tended to simplify the number of states (e.g., Mod I SPRINTER) and some extensions of the Bass model have tended to increase the number of states. The latter category includes the models proposed by Midgley (1976), Dodson and Muller (1978) and Mahajan, Muller and Kerin (1984). It is interesting to note, though, that whereas Midgley studies the diffusion process by decomposing the sales histories of the various products into adoption states (for some problems with this approach, see Silver (1984)), Mahajan, Muller and Kerin (1984) do the same by tracking customers by using panel data.

Our contention is that there is a woeful lack of research in this area. For the multistage or polynomial diffusion models to be useful it is necessary that proper data gathering and estimation procedures be developed and established (especially for durables). Although like the pre-test and test-market models, the polynomial models have the potential of providing some very useful diagnostic information about the diffusion process (e.g. sensitivity of the word-of-mouth and other marketing mix variables), it is still an empirical question whether the polynomial models generate better forecasts than the binomial models.

B. The Ceiling is Constant: The basic diffusion models assume that there is a distinct and constant ceiling, m , on the number of potential adopters. That is, the size of the potential adopters does not increase (grow) or decrease during the course of the diffusion process (Mahajan and Peterson 1978; Sharif and Ramanathan 1981; Jeuland 1981b; Kalish (1983)). The change in size of the potential adopters can be the result of certain exogenous factors (e.g. change in the number of households for the adoption of consumer durables;

economic conditions) or endogeneous factors (e.g. pricing strategy for a new product). This assumption, in our viewpoint, has become somewhat controversial in the marketing literature (Jeuland 1981b; Kalish 1983) not because of the belief that the ceiling should be constant; rather because of the lack of conceptual and empirical knowledge on what factors really cause the ceiling to increase or decrease or how this assumption should be operationalized in a particular situation. Consider, for the example, the effect of a pricing strategy on the diffusion of a new product. In the Bass model, equation (1), it can be argued that a particular pricing strategy effects the probability of adoption (i.e., $(p + \frac{q}{m} N(t))$ term in the Bass model). However, it can also be argued that a pricing strategy should impact the ceiling (i.e., $(m - N(t))$ term in the Bass model). Similar arguments can be made about the other exogenous factors (such as economic conditions, changing demographics etc.) as well as endogenous factors (such as advertising strategies, product improvements or technological changes).

We believe that further research is needed to conceptually and empirically study the implications of this assumption. A comprehensive empirical study comparing the impact of various factors on the probability of adoption and market potential to assess the predictive efficiency of diffusion models will be very useful.

C. Only One Adoption is Allowed: The basic diffusion models permit only one adoption by an adopting unit. This assumption may be valid for certain durables. However, even for these products, given their short life cycles, it is important to project replacement, repeat and multiple adoptions. In fact, in our judgment, most of the applications of the various diffusion models to consumer durables have made an arbitrary assumption regarding the length of the

first-purchase volume curve to justify the data contamination due to replacements and repeat purchases.

To our knowledge, no published model is currently available to systematically project adoptions due to replacements (for a simple illustration for estimating replacements, see Lawrence and Lawton 1981). Although Lilien, Rao and Kalish (1981) and Mahajan, Wind and Sharma (1983) have suggested extended formulations to include repeat purchase, these modeling efforts are primarily concerned with decomposing the sales history of a new product into first and total repeat purchases ignoring the depth of repeat (Eskin 1973). Similarly, the polynomial model suggested by Dodson and Muller (1978) (which does incorporate repeat purchase) also ignores depth of repeat. Its implementation, however, would require state-tracking panel data and development of proper estimation procedures.

To sum, although by definition the basic diffusion models have been primarily developed to project first-purchase sales volume curve, practical applications of these models suggest that in many situations attention needs to be devoted to extend these models to estimate replacement and repair sales.

D. Marketing Mix Strategies and Competitive Structure are Ignored: One of the major criticisms of the basic diffusion models is that they are of little use to the new product manager since they consider diffusion as a function of time only. The strategies employed by a company are not explicitly included in the models, thus inhibiting the evaluation of the effect of different strategies on innovation diffusion.

In order to put his comment in perspective, let us reconsider the basic objective of basic diffusion models. As exhibited below, consider an industry consisting of k number of competitors each producing a single brand of some

durable product. Assume that the number of adopters of brand i in time t is

n_{it} . That is, total number of adopters for the product category in time t is

$$n(t) = \sum_{i=1}^k n_{it} \text{ or the cumulative number of adopters at time } T \text{ is } N(T) = \sum_{t=1}^T n(t).$$

Firm or Brand	Time					
	1	2	...	t	...	T
1	n_{11}	n_{12}	...	n_{1t}	...	n_{1T}
2	n_{21}	n_{22}	...	n_{2t}	...	n_{2T}
.	.	.				
.	.	.				
.	.	.				
i	n_{i1}	n_{i2}	...	n_{it}	...	n_{iT}
.	.	.				
.	.	.				
.	.	.				
k	n_{k1}	n_{k2}	...	n_{kt}	...	n_{kT}
Period Sales	$n(1)$	$n(2)$		$n(t)$		$n(T)$
Cumulative Sales	$N(1)$	$N(2)$		$N(t)$		$N(T)$

The basic diffusion models, by definition, are designed to represent the growth of a product category (i.e. growth of $n(t)$ or $N(t)$). Consequently, unless there is only one firm in the industry (the case of monopoly), the basic diffusion models may not be appropriate to model the growth of a brand or examine the impact of a firm's marketing strategy on the growth of its brand. In spite of this, the basic diffusion models have been and can be extended to analyse the following situations:

(i) Relationship between product categories: Innovations are neither introduced into a vacuum nor do they exist in isolation. Other innovations

exist in the marketplace and may have an influence - either positive or negative on the diffusion of an innovation. Consequently, before projecting the growth of a product category, it is important to examine its relationship with other product categories. Four such relationships have been hypothesized by Peterson and Mahajan (1978). These are: Independent (e.g. modular housing units and electric trash compactors), Complementary (e.g. washers and dryers), Contingent (computer software and hardware) and Substitutes (black and white versus color televisions). Further empirical work on the proposed relationships is required to assess their impact on product sales.

(ii) Impact of potential adopters' perceptions of innovation characteristics: The basic diffusion models also tend to regard all innovations as equivalent units from the viewpoint of study and analysis (Rogers 1983). That is, they tend to ignore the impact of potential adopters' perceptions of innovation characteristics (attributes) on the rate of adoption. In fact, Roger (1983, p.232) has emphasized that "one important type of variable in explaining the rate of adoption of an innovation is its perceived attributes". After examining a number of studies, he has indicated that 49 to 87 percent of the variance in rate of adoptions of the various innovations is generally explained by individuals' perception of five innovation attributes -- relative advantage, compatibility, complexity, trialability, and observability. In a recent metaresearch of seventy-five research studies, Tornatzky and Klein (1982) found the strongest support for the relationships of relative advantage, compatibility, and complexity with the rate of adoption, and less support for trialability and observability. The general conclusion from these studies seems to be that it is the potential adopters' perceptions of innovations' attributes that affect their rate of adoption.

In the view of the above, it is clear that incorporation of potential adopters' perceptions of the relevant innovation attributes will be desirable in

explaining its relative rate and ultimate level of adoption. Consider, for example, the case of substitutes. The potential adopters' perceptions of attributes offered by each product category will be important in assessing their relative rate of adoption. Furthermore, such information will be useful in positioning the product category in the marketplace. One such application has been provided by Srivastava, Mahajan, Ramaswami and Cherian (1985). These authors examine the relative diffusion of fourteen investment alternatives (e.g. growth common stock, money market funds, oil and gas partnerships, equipment leasing programs, etc.) by incorporating investors' perceptions of these investments into the Bass model (see also Kalish and Lilien 1983).

(iii) Growth of a brand: The basic diffusion models provide estimates for the growth of a product category. If an independent model can be developed to forecast the market share for a brand, the sales estimates for the brand can be obtained by multiplying product category sales by the brand share estimates.

It was indicated earlier that pretest-market measurement procedures are currently available to estimate the ultimate market share for a nondurable brand (e.g. ASSESSOR developed by Silk and Urban 1978). Adaptation of such procedures to estimate market share over time for a durable brand in conjunction with the basic diffusion models will be extremely desirable in projecting the growth of a brand. Development of such a measurement methodology will also be useful in predicting the success of a new durable brand before launch. In fact, one such effort has been made by Roberts and Urban (1984). They have illustrated their approach to project the sales potential of a new car model. Further development of such approaches and their validation will enable a marketing manager to project the growth of a new or existing brand within an industry competitive structure.

(iv) Impact of marketing mix variables: Since the pioneering work of Robinson and Lakhani (1975) (incorporating the impact of pricing into the Bass diffusion model), several efforts have been made to systematically study the impact of price and advertising on the product growth (these efforts are extensively reviewed by Kalish and Sen in this volume). Since the diffusion models are primarily designed to represent the growth of a product category, these modeling efforts either implicitly assume a single brand/product industry or examine the impact of these marketing mix variables (especially price) at the industry level. Although analytically very elegant, these modeling efforts would significantly benefit by further empirical analyses. In our viewpoint, these modeling efforts have been useful in establishing working hypotheses (e.g. appropriateness of penetration versus skimming pricing strategy based on the intensity of word-of-mouth or the appropriateness of blitz/maintenance advertising strategy under the various conditions of word-of-mouth) to examine the impact of these marketing mix variables on the product life cycle.

Despite these modeling efforts, there is woeful lack of research in this area. For example, consider the marketing mix variable of distribution. How a product is made available to consumers and to whom it is made available can definitely impact the rate of adoption. In fact, a distribution strategy can be effectively used to monitor the diffusion of a product (e.g. national roll-out strategy for a new product (i.e. movies)). Further theoretical and empirical research in this area could potentially make these models appropriate to monitor and control the life cycle of a new product.

(v) Competition between the firms: Although the diffusion models are designed to represent the growth of a product category, the sales of the product category are dependent upon the number of firms and nature of competition among

firms participating in the sales of that product category. Consequently, the timing of entry and exit of various firms can significantly impact the rate of diffusion. In our viewpoint, this would be a very appropriate extension and utilization of basic diffusion models. We believe that the perspective provided by Dolan, Jeuland and Muller (1985) should stimulate further research on this topic.

Possible Uses of Diffusion Models

The statement that diffusion models work in some cases and do not perform well in others also needs some clarification. The studies concerned with the viability of basic diffusion models (e.g. Heeler and Hustad 1980; Tigert and Farivar 1981) have generally examined their applications in the context of sales forecasting. In our viewpoint, sales forecasting is only one of the objectives of diffusion models. In fact, most of the empirical studies in marketing have been primarily concerned with fitting or describing annual time-series data by using a particular diffusion model (e.g. Bass 1969; Easingwood, Mahajan, Muller 1983; Schmittlein and Mahajan 1982; Srinivasan and Mason 1985) and do not go beyond one-step-ahead sales forecasts for one or two time periods. One of the possible reasons for this is that although by definition, for estimation purposes, we need number of data points equal to the number of diffusion model parameters to be estimated (e.g. three data points to estimate p , q and m in the Bass model), empirical studies have indicated (e.g. Heeler and Hustad 1980; Srinivasan and Mason 1985) that stable and robust estimates for the parameters of the basic diffusion models are not obtained unless one uses at least eight data points including the point of inflection. Given that the first-purchase sales volume curves for the durables generally span over eight to twelve years, the validation of the diffusion models is

generally restricted to one-step-ahead sales forecasts for one or two time periods. We believe that when considering diffusion models for forecasting applications, it is first necessary to evaluate their characteristics and capabilities relative to alternative forecasting techniques that are either designed to model the product life cycle (for a review of such models, see Wind 1982, chapter 3) or to capture the unique characteristics of any time-series data (see, for example, Makridakis, Wheelwright and McGee 1983). For example, consider the simplified comparison of basic diffusion models and the Box-Jenkins approach shown in Table 1. Our objective of showing this self explanatory comparison is not to suggest that the Box-Jenkins approach is appropriate for modeling the asymptotic diffusion process, rather to highlight the types of comparisons that are required in selecting the most appropriate sales forecasting approach. In addition, such comparisons will be useful in establishing the validity of diffusion models with respect to the alternative sales forecasting approaches and to suggest directions for combining diffusion models with other sales forecasting approaches to capture the unique benefits offered by them.

In addition to forecasting, perhaps the most useful uses of diffusion models are for descriptive and normative purposes. Diffusion models provide an analytical approach to describe the spread of a diffusion phenomena. As such, they can be used in an explanatory mode to test specific diffusion-based hypotheses. The latter is illustrated by the works of Mansfield (1961), who used diffusion curves to test hypotheses about the evolution of technology, Dixon (1980), who used Gompertz diffusion model to reexamine the adoption of hybrid corn among U.S. farmers, Easingwood, Mahajan and Muller (1981), who used a flexible diffusion to test the hypotheses concerning the declining impact of word-of-mouth on the adoption of CAT scanners by U.S. hospitals and, Mahajan,

Muller and Kerin (1984) who used diffusion models to examine the impact of negative word-of-mouth on the adoption of an innovation.

Since the diffusion models are designed to capture the product life cycle of a new product, for normative purposes, they can be used as the basis of how a product should be marketed. In our viewpoint, recent research on diffusion models has mostly emphasized this important use of the diffusion models. Examples include the works of Horsky and Simon (1983), who derived an advertising strategy via the Bass model for a new product, Jeuland (1981b) and Kalish (1983), who have derived propositions concerning the pricing and advertising strategies in the presence of uncertainty about the product offerings and, Mahajan, Muller and Kerin who have derived timing strategies regarding the start and withdrawal of an advertising campaign and launching of a new product in the presence of positive and negative word-of-mouth.

To sum, the comment that diffusion models work in some cases and do not provide good results in others has been primarily made in the context of forecasting. However, forecasting is only one of the uses of the diffusion models. We believe that diffusion models can be powerful analytical tools for descriptive and normative purposes also.

CONCLUSIONS

Since the publication of the paper by Bass in 1969, a number of efforts have been made to extend his model to depict the growth of a new product. Despite these efforts, we believe that many of the criticisms of these models are valid. It is imperative that the researchers working in this area be sensitive to the comment as to why these models work in some cases and do not perform well in others. In our judgment, given the current state-of-the-art of these models,

in addition to the extensive real world applications of these models, further work is needed in the following areas:

- basic diffusion models (binomial models), like the Von Bertalanffy model, that are flexible and can accommodate various diffusion patterns and are based on clearly explicated behavioral assumptions,
- analytical procedures that can assist in linking various types of sales data (e.g. number of prescriptions written) to the number of adopters (e.g. number of physicians) and vice versa,
- measurement and estimation procedures (e.g. Bayesian approach) to incorporate management or expert judgments into the estimation procedures of the basic diffusion model parameters.
- measurement and estimation procedures to model the growth of a new product or a brand prior to its introduction.
- measurement and estimation procedures to incorporate potential adopters' perceptions of product attributes (e.g. via conjoint analysis, Green and Wind (1975)) into the basic diffusion models.
- conceptual, empirical and analytical frameworks to incorporate exogenous and endogenous factors into the measurement of the size of the market potential and/or the probability of adoption.
- conceptual and analytical frameworks to model sales due to replacements, multiple adoptions and repeat purchases.
- measurement and estimation procedures to implement multistage or polynomial diffusion models.
- conceptual and analytical frameworks to study the impact of the timing of entry and exit of firms and their competitive strategies on the growth of a product.

- conceptual and analytical frameworks to examine uncertainty inherent in innovation diffusion and to provide appropriate managerial guidance (e.g. Taperio 1983).

- empirical studies clearly demonstrating how these models can be used effectively to test diffusion related hypotheses and develop normative theory for product life cycle.

- empirical studies comparing the performance of sales forecasts developed by diffusion models to the sales forecasts developed by alternative time-series models.

- measurement and estimation procedures to examine the impact of relationships between products on the growth of a new product.

To sum, further research on the above mentioned areas can make diffusion models acceptable and viable tools to study the diffusion of an innovation.

TABLE 1**Simplified Comparison of Diffusion and Box-Jenkins****Approaches to Forecasting**

Diffusion Model Characteristics	Box-Jenkins Characteristics
Theory-based	Data-driven (atheoretic)
Short-term forecasting (2-3 periods)	Short-term forecasting (2-3 periods)
Few data points required to estimate parameters	Relatively many data points required to estimate parameters
Parameter estimation is easy	Sophisticated parameter estimation procedure required
Application is relatively straightforward	Application requires extensive judgment
Descriptive and normative applications	Descriptive applications only
Ignores idiosyncracies of time-series data (e.g., auto correlations)	Specifically designed for time-series data

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